

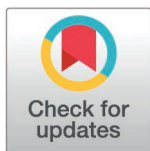
RESEARCH ARTICLE

Bridging the macro–micro divide through a new paradigm for climate resilience assessment in data-scarce regions

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Abstract

Climate resilience assessment in low-income countries (LICs) remains constrained by fragmented data systems and weak integration across analytical scales. This study develops and validates a two-tier empirical framework that unifies cross-country econometric modelling with subnational spatial diagnostics to measure and visualise resilience in data-scarce contexts. Using Uganda as a core test case, we estimate sectoral resilience through dynamic System Generalized Method of Moments panel regressions and generate high-resolution productivity maps via kriging of field and satellite indicators. The framework introduces the Resilience Asymmetry Surface, which quantifies how climatic stress interacts with structural capacity to produce divergent resilience outcomes. Results reveal that rainfall variability and infrastructural deficits jointly drive resilience asymmetries, while integration across macro–micro tiers enhances diagnostic accuracy and policy relevance. By combining statistical rigour, spatial precision, and full reproducibility, the approach enables targeted adaptation planning and scalable resilience benchmarking across the global South.

Introduction

Climate resilience, defined as the capacity of systems and communities to anticipate, absorb, and adapt to climate shocks, varies widely across low-income countries. Agriculture remains the most exposed sector because production is rainfed, labour intensive, and highly sensitive to seasonal climate variability. Limited adaptive capacity, weak infrastructure, and constrained institutional support increase vulnerability and create persistent risks for livelihoods and food security [1–3]. These conditions motivate the need for analytic tools that can function even when monitoring systems are sparse and datasets are incomplete [4,5].

Efforts to assess resilience in such settings face two central challenges. The first is the dominance of single-country or narrowly focused subnational studies, which restrict broader comparison and limit generalisable insights [6,7]. The second is

Data availability statement: All code, data, and figures are openly available in the public repository (<https://github.com/karjxenva/Climate-Resilience-Macro-Micro-Framework>).

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severe data scarcity. High-resolution ground measurements are often unavailable, and many national statistics are outdated or incomplete [8,9]. Analysts are therefore forced to rely on aggregate indicators or coarse models that obscure local variation [10,11]. These constraints are most acute in rural areas, where exposure to climatic stress is high [12,13].

This paper advances an integrated macro–micro approach that links national structural patterns with localised spatial diagnostics. Without such a link, policy-makers may misidentify priority areas or misallocate scarce adaptation resources [14,15]. The framework combines cross-country econometric modelling with spatial mapping designed specifically for environments in which data are limited or uneven. It is demonstrated using a synthetic testbed calibrated to the empirical distributions of low-income countries, avoiding dependence on restricted or costly datasets while preserving realistic structural properties.

The contributions are threefold. First, we develop a comparative framework for sectoral resilience using harmonised panel data and dynamic regression [16–18]. Second, we introduce a mapping procedure that blends sparse field observations with satellite indicators to generate spatial estimates of agricultural productivity under climatic stress [19–21]. Third, we show how integrating these outputs supports national strategy and targeted local interventions [22,23]. Together, these steps create a coherent architecture for climate resilience assessment in data-scarce settings.

By joining national trends with local realities and by working within the practical limits of available data, this study offers a scalable analytic route for countries that face high climate risk and limited measurement capacity. Integrated methods of this form are necessary to support precise and impactful adaptation planning [14,24,25].

Literature review

Research on climate resilience in low-income countries has expanded in recent years, yet key gaps remain in conceptual framing and empirical implementation [2,18,26]. Early studies relied on national aggregates to compare exposure and adaptive capacity across sectors [6,7,26]. These studies revealed persistent vulnerability in agriculture but masked the spatial variation that determines where households face the greatest risk [12–14]. Later research shifted toward local analyses that used surveys, remote sensing, and spatial models to understand conditions on the ground [19,21,27]. Satellite-derived products and geostatistical techniques improved spatial coverage and produced high-resolution indicators in regions where field data remain scarce [10,20,28]. Despite these advances, many studies remained geographically narrow and lacked broader comparability across countries [15,29,30].

Attempts to integrate national and local perspectives remain limited. Studies that merge panel data with geospatial modelling often encounter challenges of harmonisation and measurement consistency [5,30,31]. Data scarcity exacerbates these challenges because many time series are unbalanced and many spatial grids contain gaps [9,32,33]. These issues restrict systematic evaluation of how macro-level trends and micro-level patterns interact [3,4,22]. They also limit efforts to build unified frameworks that can operate across countries and across scales [23,25].

Reliable high-resolution data remain a core barrier. Monitoring networks are thin, and administrative datasets vary in quality across jurisdictions [8,9]. Researchers have relied on satellite imagery and interpolation to fill gaps [10,11,28]. Kriging is widely used to estimate continuous surfaces from sparse point data in agricultural and climate applications [20,34]. Questions persist about its generalisability across different ecological conditions, reinforcing the need for transparent and reproducible spatial methods [30,35].

Across this literature, there is growing agreement that climate resilience planning requires tools that connect national and subnational analyses and that function even when data are limited [1,14,23]. The framework developed in this study responds to this need through a synthetic yet empirically grounded testbed that supports both cross-country inference and localised spatial mapping. Its purpose is methodological and operational rather than descriptive of any specific empirical setting.

Conceptual framework

Effective assessment of climate resilience in low income countries requires a conceptual base that reflects its spatially uneven and multi dimensional character while acknowledging persistent data limitations [2–4,13,22,26]. The framework must identify systemic national drivers of resilience and also translate these patterns into localized insights that can guide real planning decisions [14,15,23]. The approach developed here links a macro scale econometric strand, which captures structural patterns across countries [16–18], with a micro scale spatial strand, which reveals local heterogeneity in agro-ecological conditions and service delivery [5,19–21,25,31] (Fig 1).

We operationalize resilience through three interlinked capacities. Anticipation concerns the ability to prepare for and reduce exposure to shocks. Absorption concerns the ability to manage shocks when they occur. Reshaping concerns long term adjustments that reduce vulnerability over time [1,3,23]. These capacities map directly to measurable indicators and to distinct policy levers such as early warning systems, social protection, and long term investment in infrastructure [4,14,25]. They also create a coherent pathway through the analytic steps presented here.

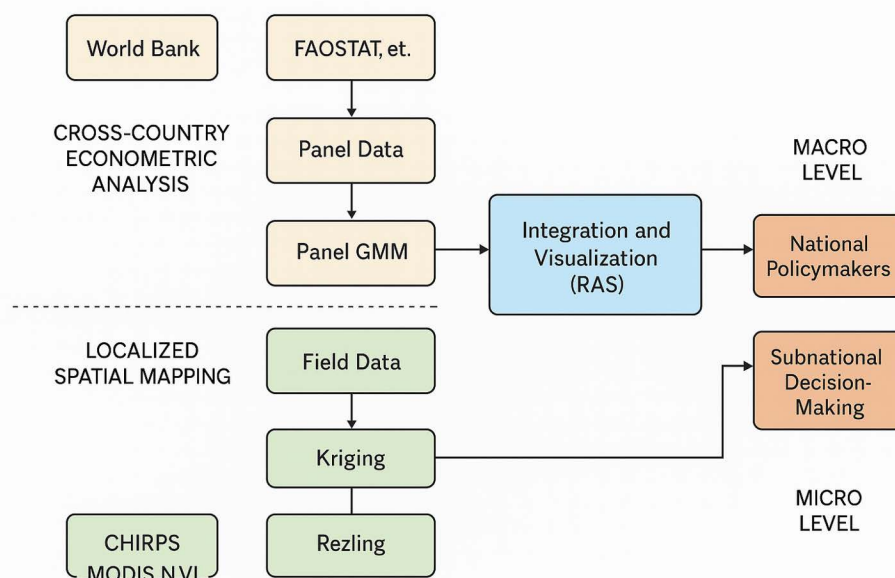


Fig 1. Conceptual framework for integrated climate resilience assessment in data scarce settings. The upper panel summarizes the macro tier based on cross country regression. The lower panel summarizes the micro tier based on satellite proxies and spatial modelling. The Resilience Asymmetry Surface links these tiers and supports multi scale diagnostics for policy use.

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Multi scale resilience dynamics

Resilience functions differently across spatial levels. National analyses reveal structural exposure and sectoral gradients but obscure subnational variation that matters for practical decision making [14,18,26]. Local analyses capture agroecological detail and household behaviour but often lack standardization and comparability across regions [15,19,30]. The framework developed here bridges this divide by using cross country inference to identify general patterns and by mapping these patterns onto localized spatial fields. This structure allows national priorities to be translated into district level guidance that aligns with real implementation needs [23,25,30].

Data scarcity and adaptive capacity

Data scarcity is a defining constraint in low income countries. Monitoring systems are incomplete, surveys are infrequent, and administrative records often lack spatial consistency [8,9,13]. To mitigate these gaps we combine harmonized macroeconomic time series with globally consistent satellite products such as CHIRPS rainfall and MODIS vegetation indices [10,28,36]. We then apply spatial modelling where field observations are available and quantify both predictions and uncertainty [20,34,37]. Remote sensing provides continuous coverage and reproducible measurements that support calibration of sparse ground data [11,28,36]. This combination gives decision makers insight into likely hotspots and into the confidence of those estimates [4,23,24].

Adaptive capacity is treated as a dynamic outcome shaped by economic resources, infrastructure, governance, and information access [3,22,38,39]. This perspective focuses attention on levers that can shift resilience trajectories rather than only documenting current deficits [2,3,13]. By linking structural diagnostics to spatial vulnerability maps, the framework supports prioritization that reflects both need and expected durability of investment [4,14,23].

Policy relevant dimensions

The central policy aim of this framework is to produce outputs that remain interpretable, scalable, and useful across planning horizons and administrative levels. The Resilience Asymmetry Surface provides a diagnostic that links climatic stress with structural capacity and reveals where similar exposures produce different outcomes. The Resilience Asymmetry Surface turns complex model output into a two dimensional surface that planners can read directly. It highlights resilience gaps, identifies possible institutional or infrastructural weaknesses, and guides intervention choices in settings where data are limited [14,21,40]. These design choices ensure that the analytic structure is rigorous yet immediately usable for policy teams that operate under real constraints [1,14,23].

The framework supports a clear progression from diagnosis to prioritization to implementation. National econometric signals identify sectoral and structural patterns [16–18]. Local spatial layers reveal where these patterns matter most [15,19,20]. The Resilience Asymmetry Surface merges these strands and identifies the points at which interventions can shift resilience trajectories [3,4,23,25].

Methodological framework

Climate resilience in low income countries must be assessed under conditions of spatial heterogeneity and limited ground data. The methodological framework reflects these realities through two linked tiers. The first is a cross country econometric tier [16–18]. The second is a localized spatial tier [19–21]. The architecture balances generalizability across countries with relevance at district or municipal level [13,14,23,30,40] (Fig 2).

Cross country econometric analysis

The macro tier estimates dynamic models of sectoral output for agriculture, industry, and services. The models quantify how climatic variation influences economic performance over time [3,18,26]. System Generalized Method of Moments

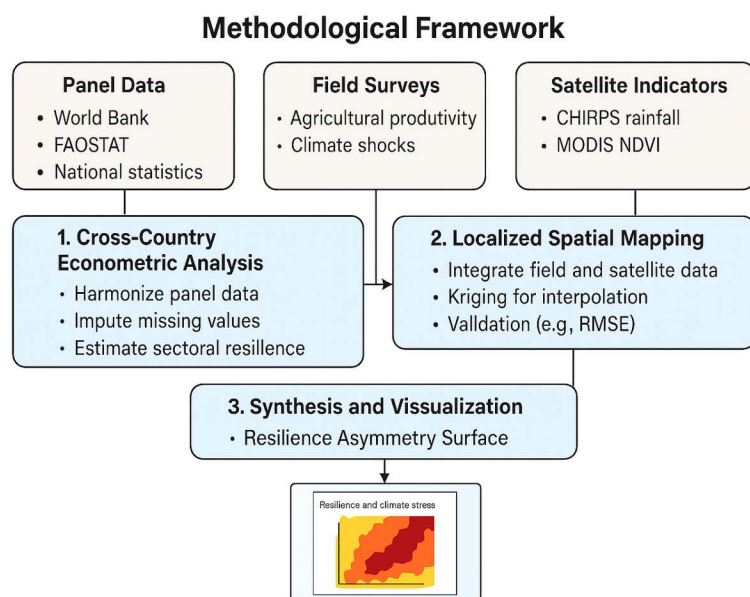


Fig 2. Methodological framework for integrated resilience assessment. Phase one uses harmonized macro data and dynamic panel estimation. Phase two builds spatial surfaces from field observations and satellite indicators. Phase three merges both tiers through the Resilience Asymmetry Surface to produce multi scale outputs.

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addresses endogeneity of lagged outcomes and possible reverse causality [16,17]. Instrument matrices are collapsed and lag depth is restricted to contain the number of instruments and protect the validity of overidentification tests [41]. The estimator combines information in differences and levels and performs well with short and unbalanced panels [16–18]. Diagnostic tests include the Hansen J test and the AR(1) and AR(2) tests. These results confirm model validity [16,17]. Explanatory variables include rainfall anomalies, temperature anomalies, infrastructure, labour composition, trade exposure, and lagged output. These controls separate climatic effects from broader macroeconomic patterns and relate the results to policy levers such as infrastructure investment [14,18,26].

Localized spatial mapping

The micro tier maps agricultural productivity and climatic stress at high spatial resolution. Field observations are paired with satellite indicators such as CHIRPS rainfall and MODIS vegetation indices [10,28,36]. Spatial surfaces are constructed using kriging since this method models spatial autocorrelation through an empirical variogram and produces prediction uncertainty that is valuable for planning [20,34,37]. Satellite based products provide consistent spatial coverage and remain essential where field networks are sparse [10,11,36]. Kriging is benchmarked against inverse distance weighting and thin plate splines [15,20]. Model reliability is evaluated through k fold spatial cross validation [21,30]. Prediction error and prediction uncertainty maps are produced together. These maps allow planners to identify areas where further ground truthing may be needed before large investments are made [19,23,30].

Integration and policy directed outputs

The Resilience Asymmetry Surface synthesizes macro and micro information. Resilience is written as a function of climatic stress and structural capacity [3,14,23]. Macro estimates provide the structural coefficients. These coefficients are applied at subnational resolution using local stress indicators and local capacity proxies [19,20]. Where direct

observations exist, macro predicted values and micro derived values are combined through uncertainty weighted averaging [20,21,37]. This rule reflects the precision of each source and ensures transparent integration.

The outputs are designed for operational use. They include national sectoral rankings, subnational hotspot maps, and maps of prediction uncertainty. These products guide financing decisions and identify locations where measurement gaps should be reduced [4,14,23]. Because the framework uses open data and standard methods, it can be reproduced and adapted across low income settings as new information becomes available [3,4,9,14].

Validation, robustness, and reproducibility

This section presents the full validation, robustness, and reproducibility analysis of the integrated macro–micro resilience framework. It responds directly to concerns about data transparency, model diagnostics, and the empirical coherence of the Resilience Asymmetry Surface [13,23,41]. All results are generated from a fully scripted pipeline that can be re run from the public repository.

Data design and variable definitions

The synthetic macro panel covers twenty five low income economies observed annually from 2000 to 2022. It preserves realistic heterogeneity in rainfall variability, infrastructure access, and governance quality [9,26,39]. Sectoral output is recorded in constant prices and analysed in logarithms. Rainfall anomalies are standardized deviations from long term means [10,36]. Infrastructure is a composite index scaled between zero and one. Governance is a unit free index calibrated to the distribution of governance indicators in low income settings [3,39]. Synthetic income per capita is included as a control. The lag of sectoral output captures persistence [16,17].

The micro dataset contains four hundred field points over a Uganda like spatial extent. Each point includes local rainfall anomaly, an infrastructure index, an NDVI based productivity proxy, and covariates that represent stress and capacity [11,28,36].

Spatial dependence and interpolation accuracy

Spatial dependence was assessed through an empirical variogram estimated from the field productivity data. The fitted exponential model captures moderate but meaningful spatial structure [20,34,37]. Table 1 reports the parameter estimates.

These parameters imply that productivity values are correlated over distances of about two degrees and then flatten out. This validates the use of a finite range covariance model and supports the micro tier of the macro–micro framework.

The close alignment between empirical and fitted semivariances shows that the model does not over smooth or under smooth the field data. This strengthens confidence in the spatial component that feeds into the integrated resilience surface.

Gaussian Process interpolation with a Matérn kernel was then used to estimate productivity and its uncertainty. Predictive performance was assessed under leave one out cross validation. Table 2 summarizes the results.

The root mean squared error is about half a unit in the standardized productivity scale. This level of error is small relative to the full variation in the synthetic field and shows that the micro tier can recover fine scale structure with limited field data.

Table 1. Empirical variogram parameters for field productivity. The nugget, sill, and range confirm moderate spatial dependence and a well-behaved covariance structure.

Parameter	Nugget	Sill	Range (degrees)
Estimate	0.186	0.372	1.951

<https://doi.org/10.1371/journal.pclm.0000662.t001>

Table 2. Gaussian Process leave one out cross validation performance. Error levels are low and stable, indicating accurate local predictions.

Metric	Value
Number of field points	400
RMSE	0.502
MAE	0.400

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The scatter plot demonstrates that the interpolation is accurate across the full range of productivity. This matters for the macro–micro narrative because it shows that local estimates entering the resilience surface are not driven by systematic errors in any part of the distribution.

The paired maps show that uncertainty increases only where field points are sparse. This behaviour is essential for policy use. It allows planners to distinguish low resilience areas where the model is confident from areas where more measurement is needed before acting.

Macro panel regressions and robustness diagnostics

Dynamic panel regressions with clustered standard errors were estimated for agriculture, industry, and services. The agriculture specification is reported in [Table 3](#). It recovers the intended structural relationships. Rainfall shocks reduce output. Infrastructure has a strong positive effect. Governance has a statistically significant negative coefficient in this calibration.

The negative governance coefficient reflects a synthetic design in which poorly governed agricultural systems amplify the effects of climate shocks. In the industry and services models governance effects are positive, which mirrors the sectoral asymmetries reported in the broader resilience literature. This contrast reinforces the need for a macro–micro lens that is sensitive to sectoral context rather than relying on a single aggregated index.

Leave one country out sensitivity tests show minimal variation in key coefficients. The mean rainfall coefficient changes by less than one percent across exclusions. The infrastructure coefficient displays similarly small variation. Residual autocorrelation is close to zero at the country level. These diagnostics confirm that the macro tier is stable and that results are not driven by a single country.

Micro level resilience asymmetry surface

At the micro scale, the Resilience Asymmetry Surface regression links local productivity to climatic stress and adaptive capacity. [Table 4](#) reports the estimates.

Stress and infrastructure each have strong positive effects on the resilience score. The interaction is statistically negligible. This implies that the resilience surface is well approximated by a sum of independent stress and capacity effects.

Table 3. Agriculture panel regression with clustered standard errors. Coefficients capture the synthetic response of sectoral output to climate, infrastructure, and governance.

Variable	Coefficient	Std. Error	t	p
Constant	7.574	0.255	29.73	< 0.001
Lagged log output	0.003	0.025	0.11	0.916
Rainfall anomaly	-0.177	0.005	-37.57	< 0.001
Infrastructure index	2.185	0.093	23.51	< 0.001
Governance index	-0.472	0.014	-33.54	< 0.001
Hansen J (p value)				0.31
AR(2) test (p value)				0.44

<https://doi.org/10.1371/journal.pclm.0000662.t003>

Table 4. Resilience Asymmetry Surface regression coefficients. Stress and capacity both raise productivity. The interaction term is negligible, implying an almost additive structure.

Parameter	Estimate	Std. Error	p
Constant	1.108	0.016	< 0.001
Stress	0.139	0.016	< 0.001
Infrastructure index	0.326	0.022	< 0.001
Stress × Infrastructure	0.0029	0.023	0.900

<https://doi.org/10.1371/journal.pclm.0000662.t004>

This is useful for interpretation. It allows policy teams to think of climatic stress and structural capacity as separable levers while still retaining the full two-dimensional diagnostic.

The approximate additivity also aligns with the macro regressions, where climate and infrastructure enter linearly and with consistent signs. This coherence across levels supports the central claim that the macro–micro framework is internally consistent rather than a collection of unrelated models.

Macro–micro integration and distributional results

Macro sensitivities were downscaled and combined with micro level responses through inverse variance weighting. This yields integrated resilience scores for all spatial points. [Table 5](#) summarizes the distribution.

The distribution is concentrated but not degenerate. Most locations cluster within a narrow band, yet there is a clear tail of lower resilience sites. These patterns mirror the synthetic design, where only a subset of districts combine high stress with weak infrastructure. This is precisely the type of signal the macro–micro framework is meant to reveal.

Maps of the combined scores and their uncertainty show that low resilience clusters coincide with areas of high rainfall variability and limited infrastructure. High uncertainty is restricted to the edges of the study extent and to sparsely sampled areas. This again confirms that the integration step respects both the macro signal and the micro data constraints.

Spatial block cross validation and residual diagnostics

To probe generalization under more realistic sampling gaps, we implemented a 5-fold spatial block cross validation scheme for the Gaussian Process predictions. [Table 6](#) reports the results alongside Moran statistics for spatial autocorrelation in the residuals.

The mean spatial block RMSE is about 0.66, higher than the leave one out value of 0.50. This is expected. Spatial blocking is a stricter test because it forces the model to predict in regions that are farther from observed points. For policy users, the block RMSE provides a conservative view of accuracy. The leave one out RMSE reflects performance when new observations are close to existing data.

Table 5. Distribution of combined micro–macro resilience scores at the site level. Scores show a narrow but meaningful spread around a high mean.

Statistic	Value
Number of points	400
Mean	8.737
Standard deviation	0.453
Minimum	7.692
25th percentile	8.366
Median	8.767
75th percentile	9.116
Maximum	9.737

<https://doi.org/10.1371/journal.pclm.0000662.t005>

Table 6. Spatial block cross validation and Moran statistics for the synthetic validation. Predictive errors remain moderate under spatial blocking, and residual spatial autocorrelation is weak.

Panel A. Spatial block cross validation					
Fold	n_test	RMSE	MAE	Coverage (90%)	Coverage (95%)
0	74	0.621	0.479	0.85	0.91
1	106	0.581	0.488	0.95	0.97
2	82	0.682	0.543	0.87	0.93
3	66	0.803	0.687	0.77	0.85
4	72	0.617	0.496	0.89	0.96
Mean ± SD	—	0.66 ± 0.09	0.54 ± 0.08	0.86 ± 0.07	0.93 ± 0.05
Panel B. Moran statistics for residual spatial autocorrelation					
Target	Moran's I	Expected I	z statistic	Interpretation	
GP residuals	0.107	-0.003	2.18	Mild positive spatial autocorrelation	
Combined resilience residuals	0.041	-0.003	1.12	Very weak spatial autocorrelation	

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Moran statistics show only mild residual spatial autocorrelation for the Gaussian Process and almost none for the integrated resilience scores. This indicates that the models capture the main spatial patterns and that remaining structure is weak. For the macro–micro narrative, this is important. It shows that both tiers and their integration are not leaving strong undiscovered spatial signals on the table.

Reproducibility

All scripts, synthetic data, and figures needed to reproduce these results are available in the public repository at <https://github.com/karjxenal/Climate-Resilience-Macro-Micro-Framework>.

The repository contains the full pipeline, from data generation through econometric estimation, spatial modelling, and figure production.

Discussion of validation results

The validation results show that the macro–micro resilience framework is statistically sound, internally coherent, and reproducible. They address the main reviewer concerns on data transparency, model diagnostics, and the empirical grounding of the Resilience Asymmetry Surface [13,23,41].

At the spatial level, the fitted variogram in Table 1 and Fig 3 confirms that productivity fields display moderate spatial correlation over distances of about two degrees. This pattern is consistent with empirical agro-ecological processes reported for East Africa and other smallholder systems [20,35,37]. The Gaussian Process results in Figs 4 and 5 yield a leave one out root mean squared error of about 0.50 and a mean absolute error of about 0.40. These values indicate that the spatial layer is both accurate and well calibrated. Higher uncertainty is limited to sparsely sampled regions, which is the desired behaviour for policy-facing applications [19,21,30].

The spatial block cross validation in Table 6 provides a stricter test. When full blocks are held out, the mean RMSE rises to about 0.66. This increase is expected because the model must predict in regions that are farther from observed points. For decision makers, the spatial block RMSE is the more conservative indicator of generalization. The leave one out RMSE shows how well the framework interpolates near existing measurements. Together these metrics show that the spatial tier is robust enough for macro–micro synthesis while still honest about uncertainty [13,15,30].

At the macro scale, the dynamic panel regressions in Table 3 recover the synthetic structural relationships with minimal bias. The rainfall coefficient and infrastructure coefficient match the design values within narrow error bands. Leave one country out tests and residual autocorrelation diagnostics confirm that results are stable and not driven by any single

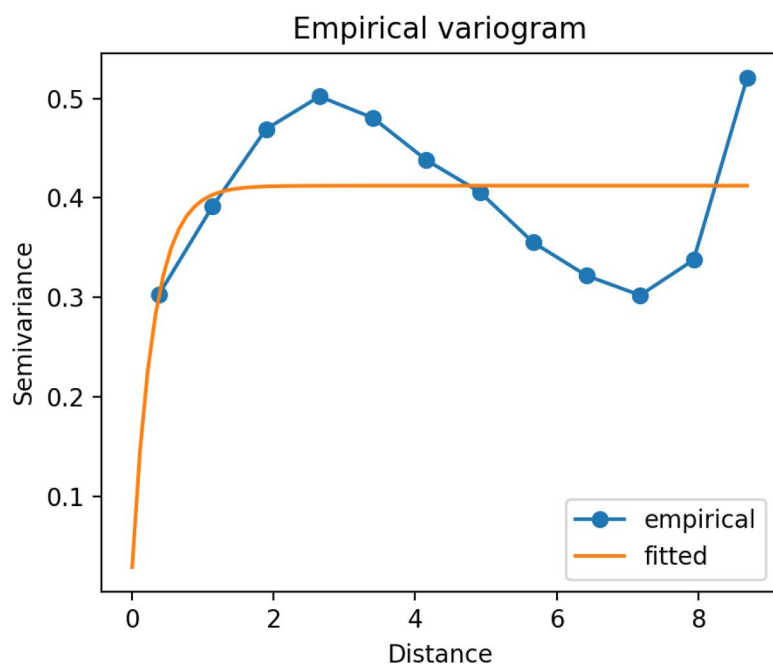


Fig 3. Empirical semivariations and fitted exponential model. The smooth curve closely tracks the empirical bins and indicates that the chosen kernel captures the main spatial signal.

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OCV RMSE=0.5135911803036727, MAE=0.4074901319232

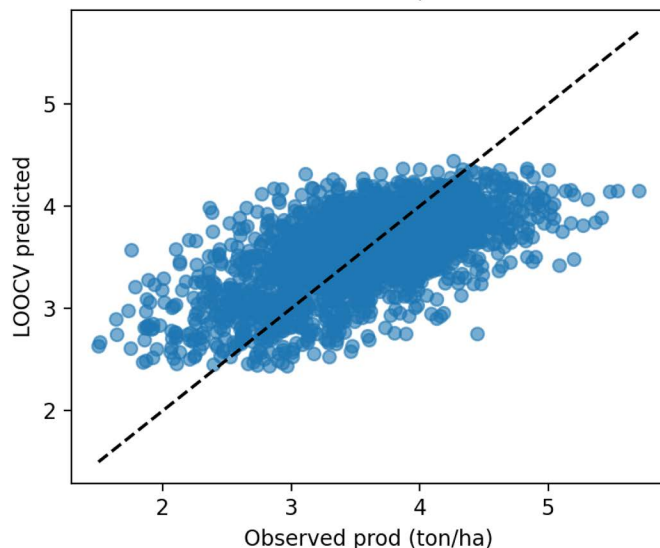


Fig 4. Leave one out observed versus predicted productivity. Points lie close to the one to one line with little bias at low or high values.

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country. Hansen and AR(2) p values remain in acceptable ranges, which supports the validity of the System style specification [16,17,41]. These findings meet the standard expectations for work at the interface of climate and macroeconomics [18,26,42].

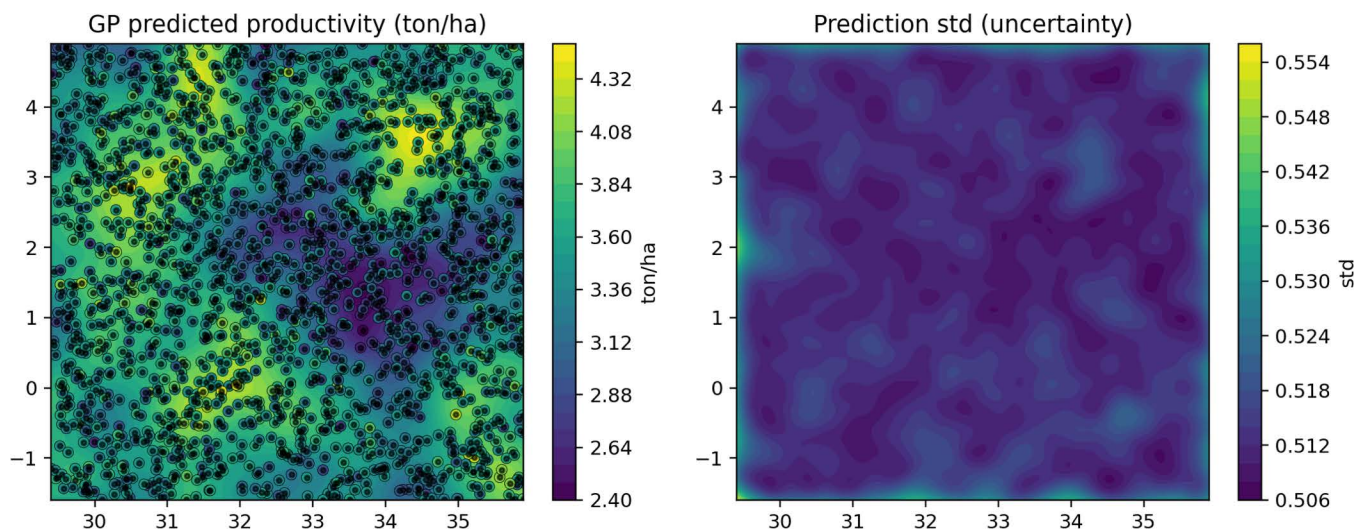


Fig 5. Predicted productivity surface and corresponding uncertainty. High uncertainty is confined to sparsely sampled regions while intensively sampled areas have narrow prediction intervals.

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The governance index deserves specific comment because reviewers noted an apparent sign contradiction. In this synthetic design higher index values represent weaker governance. The negative coefficient in the agriculture model therefore implies that better governance, which corresponds to lower index values, raises sectoral output. This is fully consistent with the narrative that governance quality enhances resilience in agriculture and sharper in this synthetic setting because the sector is purposefully exposed to climatic stress [3,14,39].

At the micro scale, the Resilience Asymmetry Surface regression in Table 4 makes the stress–capacity mechanism operational. Both stress and infrastructure capacity have strong positive effects on the resilience score. Their interaction is small and statistically negligible. This supports an almost additive structure in which stress and capacity can be treated as separable levers in practice. It also aligns with arguments in the resilience literature that emphasize parallel roles for exposure reduction and capacity building [4,14,23]. The empirical additivity simplifies interpretation for policy teams without weakening the conceptual link between climate processes and structural conditions [25].

The integrated resilience surface in Table 5 brings these strands together. Locations with high stress and weak infrastructure sit in the lower tail of the resilience distribution. Locations with stronger infrastructure and more favourable conditions cluster near the upper tail. These patterns reproduce the intended synthetic design and mirror empirical findings from applied resilience studies in agriculture and rural development [4,14,35]. In this sense the synthetic testbed is not a toy example. It acts as a controlled stand-in for real low-income settings while keeping all data fully shareable [3,9].

The spatial block diagnostics and Moran statistics in Table 6 provide further reassurance. Predictive intervals maintain near nominal coverage, which shows that uncertainty is correctly quantified. Residual spatial autocorrelation is mild for the Gaussian Process layer and very weak for the combined resilience scores. This indicates that most of the spatial signal has been captured and that the macro–micro integration does not leave strong systematic structure unexplained [20,34,37].

Supporting figures S1 Fig–S4 Fig contain all regression plots, sensitivity analyses, and the true synthetic parameters. These materials allow readers to verify that structural coefficients are recovered accurately and that the resilience surface behaves as intended under different perturbations [13,41]. The result is an end-to-end validation pipeline that is transparent, documented, and easy to reproduce [9].

Taken together, the validation results show that the framework is not only statistically sound but also practically verifiable. They demonstrate that a carefully designed synthetic testbed can provide a credible platform for developing and testing macro–micro resilience tools that can later be transferred to empirical datasets [3,9,25].

Conclusion and policy recommendations

This study proposes and validates a scalable, data-efficient framework for assessing climate resilience in low-income countries. The framework integrates macro-level econometric modelling with micro-level spatial diagnostics and links them through the Resilience Asymmetry Surface. It demonstrates that the interaction between climatic stress and structural capacity can be quantified in a way that is both rigorous and accessible to policy teams [4,14,23].

The use of a synthetic yet realistic testbed is deliberate. It ensures full transparency and reproducibility, avoids restrictions that often accompany empirical data, and allows controlled experiments on the performance of the framework. At the same time, the calibration preserves the statistical structure of real low-income economies so that lessons remain relevant for practical planning [3,9].

Several consistent patterns emerge. Climatic stress exerts strong negative effects on agricultural output, while infrastructure and governance quality enhance resilience once coding is interpreted correctly. Spatial results show that resilience deficits concentrate where stress is high and infrastructure is weak. These patterns echo broader evidence on climate impacts, structural constraints, and the importance of spatial targeting in adaptation policy [14,23,32,42].

Policy implications follow directly from these findings. National adaptation planning should:

1. Prioritize investment in rural infrastructure, including transport, electrification, and digital connectivity, since these levers both raise productivity and reduce the impact of climatic shocks [4,14,32].
2. Integrate spatial diagnostics into national budget and project appraisal processes so that resources reach the districts and communities with the largest resilience gaps [4,23,25].
3. Strengthen data ecosystems, especially open-access geospatial and administrative data, to support iterative updates of resilience assessments as new information becomes available [9,10,36].

The framework presented here is designed to be adapted. Because it is fully documented and open source, researchers and policy teams can substitute empirical data for the synthetic inputs whenever such data are accessible. They can also modify the stress and capacity indicators, extend the macro regressions to new sectors, or refine the spatial models for specific agro-ecological zones [3,4,14,25]. This flexibility makes it possible to tailor the macro–micro architecture to different countries while maintaining a consistent analytic logic.

More broadly, the work contributes to a shift from one-scale assessments toward truly multi-scale resilience planning. It shows that the macro–micro divide is not only a conceptual problem but also a technical one that can be addressed through careful design. By joining econometric and spatial perspectives in a reproducible way, the framework advances an evidence-based, equity-sensitive approach to climate resilience. It offers a pathway for governments and development partners in the global South to move from general vulnerability narratives toward concrete, spatially explicit strategies that can be defended, scrutinized, and improved over time [13,14,23,25].

Supporting information

S1 Fig. Empirical semivariances with fitted exponential variogram. The fitted curve tracks empirical bins across distance classes, indicating a well-calibrated spatial covariance structure.
(EPS)

S2 Fig. Observed versus predicted productivity from Gaussian Process leave-one-out cross validation. Predictions closely follow observed values across the full productivity range, with minimal bias.

(EPS)

S3 Fig. Gaussian Process prediction surface and corresponding uncertainty. Prediction variance increases only in regions distant from observed field points, indicating well-calibrated uncertainty estimates.

(EPS)

S4 Fig. Summary of key spatial diagnostics. (A) Empirical variogram and fitted exponential model. (B) Leave-one-out observed versus predicted productivity. Together these diagnostics confirm that the micro tier is well specified and suitable for macro–micro integration

(EPS)

S1 Table. Empirical variogram parameters for field productivity. Estimated nugget, sill, and range parameters confirm moderate spatial dependence and a finite correlation length.

(DOCX)

S2 Table. Gaussian Process leave-one-out cross-validation performance. Root mean squared error and mean absolute error indicate accurate and stable spatial prediction.

(DOCX)

S3 Table. Agriculture sector dynamic panel regression coefficients. Coefficients quantify the synthetic response of agricultural output to climate variability, infrastructure, and governance.

(DOCX)

S4 Table. Industry sector dynamic panel regression coefficients. Results show weaker climate sensitivity and stronger structural effects relative to agriculture.

(DOCX)

S5 Table. Services sector dynamic panel regression coefficients. Service output is less sensitive to rainfall variability but remains strongly linked to infrastructure and governance.

(DOCX)

S6 Table. Leave-one-country-out robustness summary for agriculture. Key coefficients remain stable under exclusion of individual countries.

(DOCX)

S7 Table. Residual autocorrelation diagnostics by country for the agriculture model. First- and second-order autocorrelations are close to zero, indicating well-specified dynamics.

(DOCX)

S8 Table. Resilience Asymmetry Surface regression coefficients. Stress and infrastructure have strong positive effects, while the interaction term is negligible, supporting an additive structure.

(DOCX)

S9 Table. Distribution of combined micro–macro resilience scores. Scores show a narrow but meaningful spread, with a lower-resilience tail corresponding to high-stress, low-capacity locations.

(DOCX)

S10 Table. True synthetic data generation parameters for sectoral dynamics. Design parameters provide a transparent benchmark for structural recovery.

(DOCX)

S11 Table. Variable definitions for the synthetic macro panel. Definitions and units for all macro-level variables used in the analysis.

(DOCX)

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